Wavelet Entropy Analysis of the High Resolution ECG

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Abstract

The High Resolution ECG (HRECG) is a method of detecting microvolt cardiac signals from patients who have Myocardial Infarction. These signals are called Ventricular Late Potentials (VLPs). They appear as fractionated signals with irregularity in shape on the body surface. In this study, the Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT) were used for analysis of the HRECG from the patients with and without VLPs. Then the wavelet entropy was applied to the HRECG. A disordered behavior of the system provides a high entropy value. Observations of the preliminary results in this study showed that the HRECG of patients with VLPs seems to have higher wavelet entropy than those without. In addition, the energy based on the CWT coefficient was computed. It was shown that the patient with VLPs would appear to have lower energy within the terminal QRS complex than the patient without.

1 Introduction

The heart is one of the most important organs within the human body. It can generate electrical potentials which can be recorded on the skin via surface electrodes. Patients with heart diseases have any disturbance in the depolarization conduction system within the myocardium muscle, resulting in very small cardiac signals called Ventricular Late Potentials. The studies in clinical cardiolog have shown that the occurrence of VLPs is prevalent in post-Myocardial Infarction (MI) patients at risk of developing Ventricular Tachycardia. Hence the detection of VLPs has become a topic of great interest in cardiology for over three decades. The standard method for detecting VLPs was proposed by Simson [1]. It is difficult to detect VLPs because they are normally masked by noise and motion interference, however they can be revealed from the High Resolution ECG. In the HRECG, the X, Y, and Z leads on the body surface are recorded. Patients after Myocardial Infarction who have VLPs may develop cardiac arrest. The necessity of early detection of VLPs is to give an advance warning for immediate treatment of patients and also prevent the patients from sudden cardiac death. VLPs appear as fractionated signals with disordered pattern and the concept of entropy has proven to be useful in revealing the disordered activity of a signal. Many researchers have studied time-frequency techniques such as the Short Time Fourier Transform and Wigner Distribution for the detection of VLPs [2,3]. In this study, the Continuous Wavelet Transform and Discrete Wavelet Transform were utilized to analyze the High Resolution ECG and then the wavelet entropy was applied to the CWT and DWT of the HRECG. The objective of this paper was to investigate the application of the CWT and DWT based wavelet entropy for characterization of patients with VLPs and those without.

2 Materials and Method

2.1 Data Collection

High Resolution ECG recordings were acquired from patients after Myocardial Infarction using XYZ leads. In this study, patients with VLPs and patients without VLPs were investigated. The HRECGs were recorded with patients in the supine position. Electrodes were placed on the body surface of the patient. They were applied in the standard orthogonal XYZ lead arrangement. The X electrodes are at the right and left midaxillary lines in the fourth intercostal space. The Y electrodes are placed at the suprasternal notch and the proximal left leg. The Z electrodes are at the fourth intercostal space near the left sternal margin and the back on the left side of the vertebral column. The analog signals from the XYZ leads were digitally converted at a sampling rate of 1 kHz with a resolution of 12 bits. The digital signals were transferred to a computer for further processing.

2.2 Continuous Wavelet Transform

Recently, the wavelet transform has been considered as the powerful technique for time-scale analysis of a signal and has shown potential in biomedical signal processing [2,3,4]. It provides varying time-frequency resolution. It is defined as:

$$CWT(a,b) = \int_{-\infty}^{\infty} s(t)\ \psi_{a,b}(t)dt \qquad (1)$$

where *s(t)* is the signal, $\psi(t)$ is the mother wavelet, *a* and *b* are the scale and translation parameters respectively, and *t* is the time. A wavelet family $\psi_{a,b}$ is the set of elemental functions obtained from dilations and translations of a mother wavelet ψ.

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad (2)$$

The wavelet is contracted at smaller scales, thus the wavelet transform can detect the high frequency components of the signal. This property of the CWT is well suited to the analysis of high frequency information of VLPs [2,3,4]. The CWT represents a signal in the time-scale plot because it is computed in terms of scale instead of frequency.

2.3 Wavelet Entropy

The concept of entropy has been widely used as a measure of disorder of a system. The wavelet entropy computed from the wavelet transform has been applied to the electrical brain signal [5]. In our previous studies [6,7,8], the wavelet entropy was processed for the fractionated signals obtained from the CWT coefficients. In this study, the wavelet entropy was calculated from the vector magnitude CWT and DWT. Energy (*Eij*) of the HRECG signal in the time-scale domain was calculated for each time *i* and scale *j*. Next, the probability distribution of energy for each scale was obtained as in Equation 3.

$$P_{ij} = \frac{E_{ij}}{E_i} \qquad (3)$$

where P_{ij} is the probability distribution at time *i* and scale *j*. E_{ij} is the energy at time *i* and scale *j*. E_i is the energy at time *i*. The wavelet entropy (*W*) is defined as in Equation 4.

$$W = -\sum_{j=1}^{N} P_{ij} \times \log_2 P_{ij} \qquad (4)$$

2.4 Discrete Wavelet Transform

The Continuous Wavelet Transform operates at every possible scale and time position, whereas the Discrete Wavelet Transform can perform at powers of two of scales and time positions, so called dyadic scales and positions where $a=2^j$, by using filters proposed by Mallat [9]. The procedure of such filters is very efficient for DWT algorithm implementation of signal analysis. In the Discrete Wavelet Transform, *s(t)* is decomposed on different levels as follows:

$$s(t) = \sum_{k=-\infty}^{\infty} c_J(k)\phi_{J,k}(t) + \sum_{j=1}^{J}\sum_{k=-\infty}^{\infty} d_j(k)\psi_{j,k}(t) \qquad (5)$$

where $\psi_{j,k}(t)$ is the wavelet function, $\phi_{J,k}(t)$ is the scaling function, $d_j(k)$ are the detailed signals (wavelet coefficients), and $c_J(k)$ represents the approximated signal (scaling coefficients) at each level decomposition *j*. The DWT has the capability of decomposing a signal of interest into an approximation plus detail information. It can thus analyse the signal at different frequency ranges with different resolutions. The DWT is implemented by means of a pair of digital filter banks where the signal is successively decomposed. The two filters are a high pass filter and a low pass filter. Scaling function and wavelet function, which are associated with low pass and high pass filters respectively, are used in the DWT algorithm. These filters provide the decomposition of the signal with different frequency bands by recursively applying filters to the signal. The signal is then split equally into its high and low frequency components, called details and approximations respectively. In the DWT algorithm, The input signal *s(t)* is first passed through the high pass filter and low pass filter, and subsequently the outputs of both filters are decimated by a factor of two. The input signal to the filters is the HRECG signal. The high pass filtered data set is the detail coefficients at level 1 and the low pass filtered data set is the approximation coefficients at level 1. This process can continue for further decomposition at level 2,3,4, until the limit of data length is reached. It is possible to reconstruct the original signal from the approximation and detail coefficients.

3 Results

Both the CWT and DWT were investigated to study a dynamic behavior of VLPs and the wavelet entropy was explored as a measure of a disordered pattern of VLPs. The CWT and DWT were first computed for each digitized XYZ lead and then each computed XYZ lead was combined to form a vector magnitude CWT and DWT in the time-scale domain. Then the wavelet entropy was applied to the vector magnitude CWT and DWT. The wavelet entropy obtained from the CWT and DWT was computed and normalized for patients without VLPs and patients with VLPs. Thus the wavelet entropy can be viewed as a function of time. Figures 1 and 2 show the CWT based wavelet entropy for the patient without VLPs and the patient with VLPs respectively. The vertical solid lines mark the R wave and the QRS end point. In Figures 1 and 2, the observable difference between two patients can be obtained. It can be observed that the wavelet time entropy of the patient without VLPs between the R wave and the QRS end point tends to be low, whereas the wavelet time entropy of the patient with VLPs seems to be high especially within the terminal region of the QRS complex. Because the CWT provides the energy distribution of the signal in the time-scale plot, energy computation can be performed from the CWT coefficients.

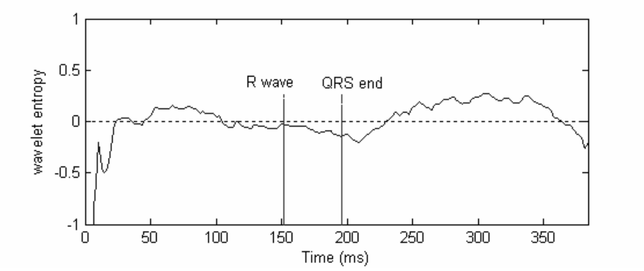

Figure 1 The wavelet entropy computed from the CWT for the patient without VLPs.

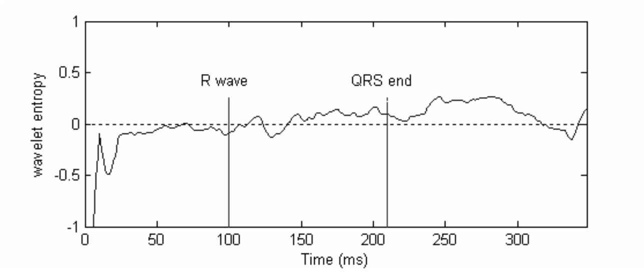

Figure 2 The wavelet entropy computed from the CWT for the patient with VLPs.

Figures 3 and 4 illustrate the CWT energy for the patients without and with VLPs respectively. In Figures 3 and 4, it clearly indicates that there is a significant difference of the resulting energy between two patients. When the energy between the R wave and the QRS complex of each patient was inspected, it was observed that the patient without VLPs has higher energy in the terminal region of the QRS complex than the patient with.

In addition, in this paper, decomposition of VLPs at level 5 was performed by the DWT and then the wavelet entropy was applied. The DWT based wavelet entropy was calculated for the patient without VLPs and the patient with, as shown in Figures 5 and 6 respectively.

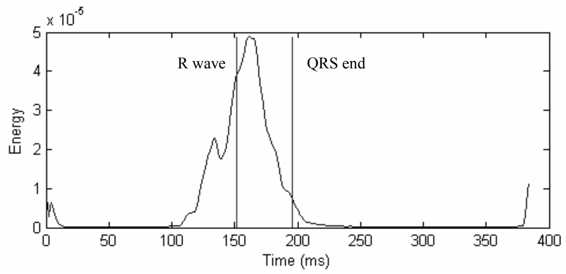

Figure 3 The energy computed from the CWT for the patient without VLPs.

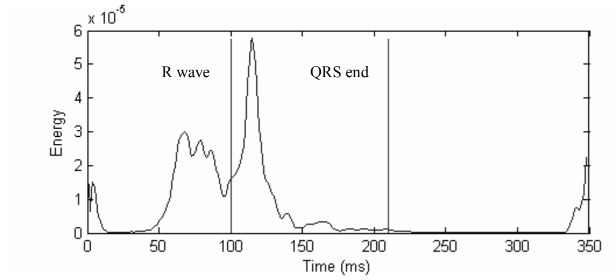

Figure 4 The energy computed from the CWT for the patient with VLPs.

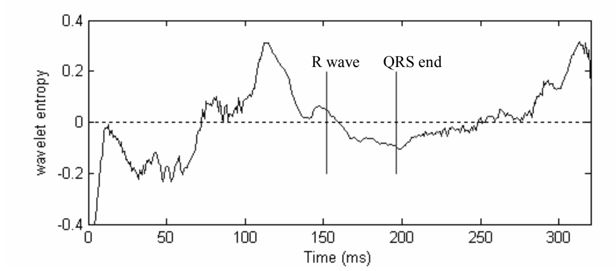

Figure 5 The wavelet entropy computed from the DWT for the patient without VLPs.

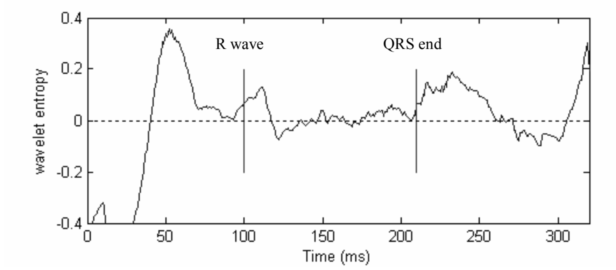

Figure 6 The wavelet entropy computed from the DWT for the patient with VLPs.

As with the CWT based wavelet entropy, the wavelet entropy derived from the DWT showed the similar pattern. In Figure 5, it was shown that the patient without is likely to have decreasing wavelet entropy between the R wave and the QRS complex. It should be noted that a remarkable decrease of the wavelet entropy was at around time 200 ms, corresponding to the QRS end point, and then an increase was seen after the QRS end point. In Figure 6, the patient with VLPs appears to have increasing wavelet entropy between the R wave and the QRS complex.

4 Discussion and Conclusion

Many studies have shown that VLPs are closely related to the presence of sustained ventricular tachycardia in patients after Myocardial Infarction that causes sudden cardiac death. Thus detection of VLPs is of great importance and they have been used as a predictive indicator for these patients in order to give a warning sign of fetal heart failure.

In this study, the application of wavelet analysis to the HRECG was investigated and then the wavelet time entropy obtained from the wavelet coefficients was computed. Entropy is related to the degree of irregularity of a signal. A signal with regular patterns has a low entropy value but a disordered signal shows a high entropy value. The wavelet entropy as a function of time for the characterization of VLPs was studied. Results showed that the patient with VLPs seems likely to have larger wavelet entropy at the terminal region of the QRS complex. Thus the wavelet time entropy would be utilized to describe the dynamic behavior of VLPs. It seems that the wavelet time entropy is likely to detect the disordered pattern of the energy distribution from VLPs in the time-scale plot. It maybe concluded that the energy distribution within the terminal segment of the QRS complex from the patient with VLPs was nonuniform due to the presence of VLPs. This result is what would be expected because of irregularity of VLPs.

In a normal heart, propagation of the energy can travel through the myocardium easily and homogeneously, thus resulting in the high energy. In a damaged heart, the energy cannot be transferred within the myocardium easily, thus the low energy was produced. Results of the CWT energy showed that the patient with VLPs would appear to have lower energy within the terminal QRS complex than the patient without.

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